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Comparison of Symmetrical, Asymmetrical, and Logarithmic Models Using GARCH, GJR-GARCH, and EGARCH Method in Forecasting Indonesia–USA Currency Volatility

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Abstract

Aim: The main object of this study was to present a comparison between GARCH models, i.e. the standard GARCH model, asymmetric GJR-GARCH, and logarithmic EGARCH on exchange rate (IDR/USD) volatility.

Methodology: The authors used GARCH, Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) and Exponential GARCH (EGARCH) in estimating and forecasting exchange rate volatility. The variables were IDR/USD, Jakarta Stock Exchange Composite Index (JCI), World Oil Price, and Nominal Broad U.S. Dollar Index, while the data were daily, taken from World Bank, Federal Reserve Economic Data, and Indonesian Stock Exchange during 2006-2025.

Results: The results revealed that in the GARCH method, there was high persistence of volatility, and the shocks were of long-lasting duration, but the model was symmetrical. The GJR-GARCH model showed that negative shocks have larger effects than positive shocks on IDR/USD but with problematic negative coefficients. Lastly, in the final comparison it was revealed that the EGARCH specifications were the most reliable in capturing asymmetric volatility dynamics, with strong evidence of leverage effects where negative shocks increase future volatility more than positive shocks.

Implications and recommendations: As IDR/USD volatility took a long time to dissipate, and negative shocks had a significantly larger effect than positive shocks, this meant that the market reacted stronger on depreciation rather than on appreciation. Therefore, it was becoming essential for policymakers in Indonesia to provide an asymmetrical policy framework to prevent the negative shocks extending into a prolonged period of distrust by the market towards IDR. One of the actions to be taken was to increase interest rate. This was a preventive action to respond to depreciation, and at the same time acknowledging the asymmetric approach to responding to depreciation.

Originality/value: The study compared three GARCH models to examine and forecast IDR/USD volatility, choosing one more statistically and economically reliable which makes this study unique. The findings present a comprehensive and methodologically established comparison that is unbiased and shows each model's limitations and strengths. The study also provided additional contributions regarding integration of broad variables into the models, with the use of world oil price, JCI, and Nominal Broad US Index as variables.

Keywords: volatility, GARCH, GJR-GARCH, EGARCH, exchange rate, negative shocks

1. Introduction

Volatility pertains to the disparity of observed returns over a specific period (Abd Rahman et al., 2023). In terms of executing an estimation and forecasting exchange rate volatility, it is essential to note that the persistent occurrence of heteroscedasticity in the data means that the Autoregressive Moving Average (ARIMA) method cannot be applied (Sabkha et al., 2020). Time-series data with heteroscedasticity taking place, means that the data were not only impacted by past value but also showed a dispersed variance of errors. Over time, studies were conducted to further develop a model which took into account both past squared errors and past conditional variances. With regard to overcoming the research limitation from the occurrence of heteroscedasticity, previous research applied methods that were constructed specifically for data with heteroscedasticity (Ezzebsa et al., 2023; Sharma et al., 2021; Wang et al., 2022). Thus, it was vital to conduct the study using an estimation method with which variance with heteroscedasticity could be accommodated (Ochoa & Sosa, 2021).

In 1982 the first introduction of the Autoregressive Conditional Heteroskedasticity (ARCH) model was proposed by Engle (Engle, 1982). Further improvements were made in the ARCH model into what was known as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The standard GARCH model that was implemented by economists over the years involved volatility modelling presented symmetrical volatility as assumption (Bollerslev, 1986). Symmetrical volatility did not put into account the leverage effect on the data, whereas the asymmetrical volatility differentiated positive and negative effects on the variable. Therefore, the GARCH method did not distinguish whether the fluctuations were moving towards a decline or a rise, and how the changes in movement would impact the variable (Ockiya et al., 2023; Dinga et al., 2023). As the degree of the depth of impact from the volatility was not incorporated into the GARCH method, hence the earlier research introduced improvements.

The Golsten, Jagannathan, and Runkle GARCH (GJR-GARCH) model was proposed to overcome the symmetrical situation in the previous standard GARCH model (Apriva Hidayana & Napitupulu, 2021; Chalissery et al., 2022; Pasaribu & Sa'adah, 2025). Next, Exponential GARCH (EGARCH) was designed to improve the results of estimations carried out by previous GARCH models. The symmetrical assumption was replaced by asymmetrical ones, also changing the arithmetical form of conditional variance into logarithmic form (Dukundane, 2023). The logarithmic form makes room for the model to react to positive or negative impacts, as volatility tends to move upward or downward in its fluctuations (Olamide et al., 2022). Therefore, GARCH models that emerged after the first discovery in 1982 further explored the depth of volatility models of the data.

In this study, the author used exchange rate to illustrate volatility. The Indonesia-USA exchange rate was represented formerly by IDR/USD, which was a calculated value to reflect the price of one country in terms of another (Suwondo et al., 2025). Across the global foreign exchange market, speculations and assumptions resulted in volatility (Umoru, Akpoviroro, et al., 2023). As such erratic movements in the currency exchange value occurred historically, it is difficult to predict the direction in which the fluctuations would be going (Suwondo et al., 2025). The tendency to depreciate or appreciate, as well as the impacts of each movement are not set in stone, even though exceptions do happen in countries with monetary authorities whose role is to establish its currency state as a fixed value. Over time, the currency exchange value between Indonesia and the USA (IDR/USD) has been showing rapid movements in both appreciation and depreciation. In the USA, in terms of currency exchange value between countries, there was not only an official exchange rate but also a nominal broad currency index (Suwondo, 2023). This reflected the international trade activity between the USA and other countries, measured as currency index.

The main objective of this study was to present a comparison between the GARCH models, namely the standard GARCH model, asymmetric GJR-GARCH, and logarithmic EGARCH on exchange rate (IDR/USD) volatility. By following the structure of this approach, the estimation results present a comprehensive and methodologically established comparison that is unbiased and acknowledges each model's limitations and strengths.

2. Literature Review

2.1. Exchange Rate Volatility

Measuring exchange rate value did not come from just one calculating factor, but several (Steinbach, 2021). The exchange rate reflects the value of currency in a country in terms of another country's currency and thus is measured not only by the price of goods between countries, but also the price in financial sector such as asset price, portfolio optimisation, risk management, and varieties of economic decisions (Heriqbaldi et al., 2023). As well as other financial asset performances, the volatility of an exchange rate was derived from the standard deviation of movements of exchange rates (Sein & Sah, 2025), whereas the exchange rate system itself reflects the flexibility of monetary authority of the country, as well as its policy framework. In terms of policy framework, the authorities are required to enrich the elements of policymaking by exploring several perspectives. Volatility poses significant challenges when policymakers navigate the exchange rate dynamics to mitigate the effect that may arise from it (Audi, 2024).

Moreover, the value of exchange rate is calculated not only from asset prices, but also from trade activities between countries (Angraini et al., 2024; Makore & Chikutuma, 2025). Several studies contributed to the discussion in which exchange rate volatilities and economic trade between countries causally influence each other (Borowski & Jaworski, 2024; Heriqbaldi et al., 2023; Makore &

Chikutuma, 2025; Sein & Sah, 2025). Therefore, the topics around which data better represent the trade-weighted exchange rate of a country to its counterparts are increasing, and research could incorporate the Nominal Broad US Index, which is a trade-weighted value of US exchange rate in terms of other countries (Almisshal, 2021; Yilmazkuday, 2025), crucial to reflect the value of US currency in terms of others, after including trade activities between countries into its calculations.

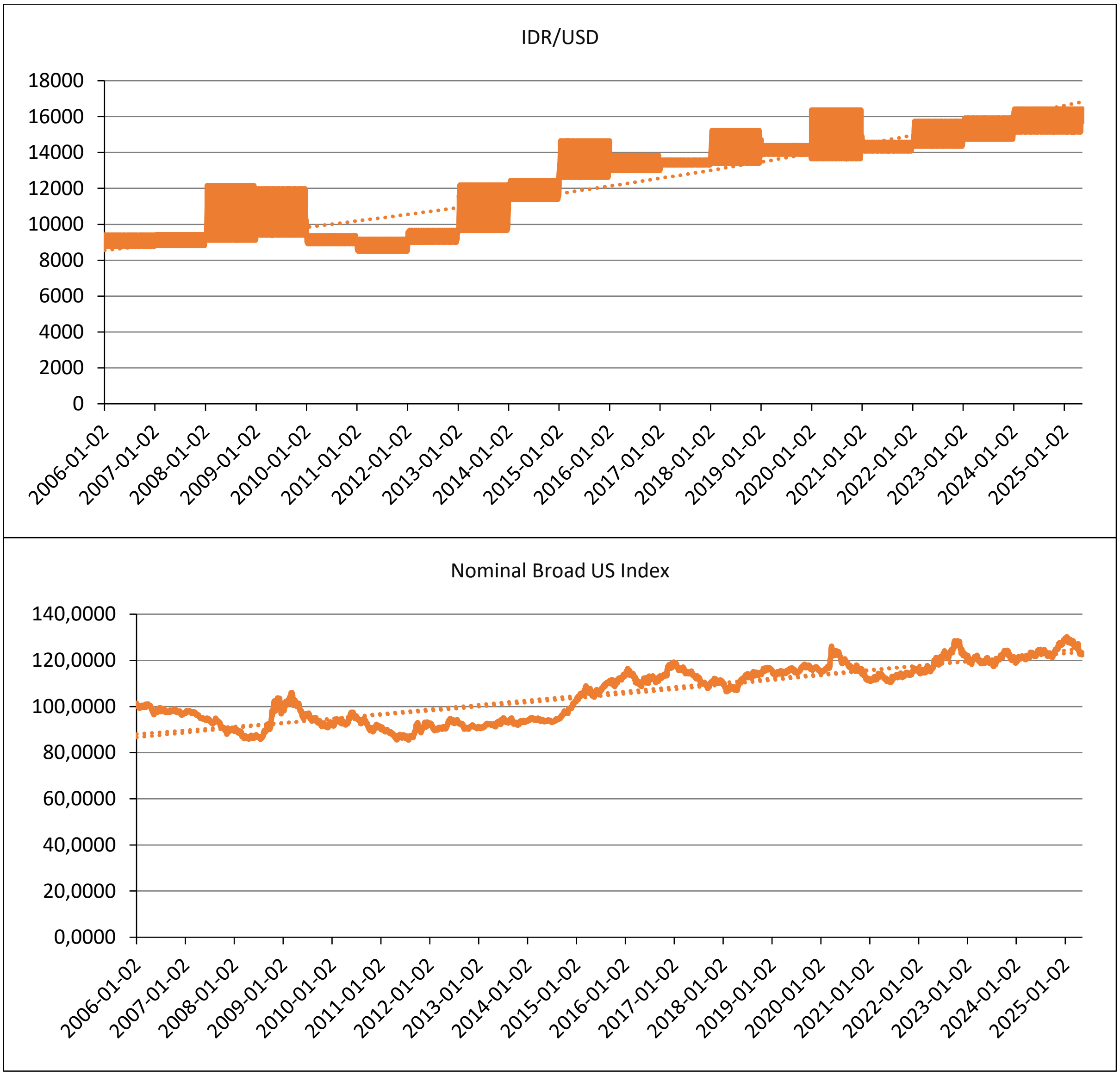


Fig. 1. The Volatility of IDR/USD and Nominal Broad US Index

Source: authors' computations using data from the World Bank, 2025.

Figure 1 shows the fluctuations and trends of the IDR/USD and the Nominal Broad US Index from 2006 to 2025 using daily data. The IDR/USD graph showed a clear upward trend meaning that IDR was depreciating over time. When the IDR/USD rate moved upwards, USD was appreciating compared to IDR. There were several points when the fluctuations seemed insignificant as the movements were minimal, but there were some skyrocketing movements as well. On the other hand, the Nominal Broad US Index also revealed significant major upward trends, which in this case did not represent a huge depreciation of its currency, but a trajectory of growth in economic performance in terms of international trade with other countries. It meant that US economic performance represented by the US Broad Index was triumphant over the years (Suwondo et al., 2023).

2.2. Comparison of GARCH, GJR-GARCH, and EGARCH Methods

The assumption surrounding modelling time series in the classical method was that the conditional variance of the prediction was time-invariant (Dinga et al., 2023). Such things do not apply in practice, because the conditional variance of volatility of time series data tends to vary over time, or in this case it is heteroscedastic. After being first proposed by Engle and then improved by Bollerslev (Eniayewu et al., 2024), the ARCH and GARCH models continued to transform into a better approach of capturing leverage effects commonly portrayed by financial and monetary data due to its asymmetry. The Glosten-Jagannathan-Runkle GARCH as well as the Exponential GARCH were introduced shortly afterwards to provide better methods to incorporate leverage effect into the estimation model. The leverage effect has a different impact on the model depending on the negative or positive movement of the volatility which occurred in the data (Chen, 2023; Lim et al., 2023). While the standard GARCH models did not indulge in this effect, other GARCH models (such as GJR-GARCH and EGARCH) provided asymmetrical assumptions to capture this effect.

Modelling exchange rates using both symmetrical and asymmetrical conditional heteroscedasticity methods was conducted by researchers during the last few decades. Hansen discovered that while various complex volatility models existed, the simple GARCH with order p, q (1,1) model was extremely difficult to outperform in out-of-sample forecasting, especially when using superior statistical tests that account for model uncertainty (Hansen & Lunde, 2005; Syamad & Handoyo, 2023; Suwondo, 2025). In contrast, several studies concluded that running different GARCH methods showed that EGARCH was the most fitting method to execute estimation while incorporating leverage effect into consideration, as EGARCH provided more heavy nuanced results with focusing on the different effect that positive and negative volatility had on the model (Villatoro, 2015; Ochoa & Sosa, 2021; Almisshal, 2021; Ockiya et al., 2023; Ganczarek-Gamrot, 2011).

To sum up, the study by (Villatoro, 2015) used two GARCH models, i.e. the standard GARCH model and the Beta-T-EGARCH model. The research found the limitations of the standard GARCH model, which was symmetrical, meaning that the model predicts future volatility without regarding positive or negative movements, which essentially ignored the differences of the impact that the model might have. Ockiya et al. conducted a comparison between the standard GARCH model, GJR-GARCH, EGARCH, and APARCH on financial data (S&P500) as well as a monetary one (exchange rate volatility) to perform a comprehensive evaluation on each model's performance in estimating volatility (Ockiya et al., 2023). Ockiya used a Dummy in GJR-GARCH to capture additional impact produced by negative impacts, and a logarithm of variance in EGARCH to provide an asymmetrical response to positive and negative impacts, as well as a large number of parameters in the APARCH model to capture the asymmetrical volatility in a more flexible way.

Moreover, previous studies revealed that stock price index was the indicator variables that impacted on exchange rate volatility (Khoury et al., 2024; Kiliç, et al., 2023; Trabelsi & Bahloul, 2022). These studies also included ARCH models, excluding that by Trabelsi & Bahloul (2022) who used MSVAR as an estimation approach. Besides the stock price index, the world oil price was also a prominent component in other studies (Hamida & Nasr, 2024; Mușetescu et al., 2022; Tri-Wahyudi & Rahmawati, 2025; Umoru, Effiong, et al., 2023). These research findings highlighted that the exchange rate responds significantly to oil price shocks, but not in a uniform way. Lastly, studies focusing on the Nominal Broad US Index as a core variable regarding exchange rate volatility found that monetary indicator (one of them being exchange rate) were highly affected by the performance of Nominal Broad US Index (Avdjiev et al., 2018; Hong et al., 2018).

3. Methodology

3.1. Variables

The data used in this study were secondary, consisting of 5,049 daily data collected from the World Bank, Federal Reserve Economic Data, and the Indonesia Stock Exchange. The study covered the period from 2006 to 2025, selected to ensure methodological rigor, to commit to data consistency, and to capture a comprehensive range of monetary and market regimes in Indonesia. Previous research discovered that in the GARCH method, models obtained using a large number of observations showed autocorrelations lower than in small samples, which would imply that in small samples there could be serious convergence errors from the negatively biased ARCH and GARCH estimates (Bianchi et al., 2020; Hwang & Valls Pereira, 2006). GARCH models require long time series to reliably estimate persistence parameters and asymmetry coefficients (in this case, with EGARCH specifically). The other reason behind the selected period was for sustaining data consistency, especially for the US Nominal Exchange Rate Index (USD Broad Index). This particular key control variable, constructed using a consistent methodology, has been employed by The Federal Reserve only since 2006.

The four variables in this study are:

- US Dollar exchange rate against the Indonesian IDR (IDR/USD)
- Indonesia Stock Exchange Stock Price Index (JCI/IHSG)
- World Oil Price (Brent Europe, Dollars per Barrel)
- US Nominal Exchange Rate Index for Trade with Indonesia (USD Broad Index)

The selection of variables in this study was guided by the characteristics of the Indonesian economy as an emerging market, as well as theoretical considerations from previous studies. The US Dollar exchange rate against the Indonesian IDR (IDR/USD) represents the currency in Indonesia, particularly given that US holds a dominant role in international trade and finance in the world. For other variables, previous research revealed that stock price index and oil price had impact on exchange rate volatility, both in IDR and other currencies (Hamida & Nasr, 2024; Khoury et al., 2024; Kiliç, et al., 2023; Mușetescu et al., 2022; Trabelsi & Bahloul, 2022; Tri-Wahyudi & Rahmawati, 2025; Umoru, Akpoviroro, et al., 2023). And as the last variable, the USD Broad Index was incorporated both to portray as well as isolate the global component of USD to IDR, to better distinguish between IDR volatility driven by external shocks or domestic ones.

3.2. Model Specification

GARCH Equation:

- the Mean Equation (dependent variable= IDR/USD)

$$Y_t = \propto + \beta \sum_{t=1}^{5,049} [w_{t-i} + x_{t-i} + z_{t-i}] + \varepsilon_t, \tag{1}$$

where n was 5,049 as shown above, and Y_t the dependent variable, which was IDR/USD, while w_t was IHSG or the Jakarta Stock Exchange Composite Index (JCI), x_t was the world oil price, z_t was the Nominal Broad US Dollar Index (the trade weighted of USD, i.e. the value of the United States dollar relative to other world currencies, and in this case Indonesian IDR). The last variable ε_t stands for error/disturbance term, or white noise occurring during the estimation.

- the Variance Equation was

$$\sigma_t^2 = c + \beta_1 \sigma_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 + \vartheta_t \,, \tag{2}$$

where variable $\beta_1 \sigma_{t-1}^2$ was for the GARCH model, and variable $\gamma_1 \varepsilon_{t-1}^2$ was for RESID $(-1)^2$ or residual from the estimation. The estimation conducted in this paper was not only for assessing autoregressive moving average equation for time-series data, but also for estimating the inconstant residual or variance of the data, which was why the author included Variance Equation.

While GARCH conducted its estimation using symmetrical assumption to its revelations, the GJR-GARCH Equation was using asymmetrical assumptions, shown in equation (3)

$$\frac{IDR}{USD_t} = \propto + \theta_1 \frac{IDR}{USD_{t-1}} + \beta_1 \mu_{t-1}^2 + \gamma_1 \, \mu_{t-1}^2 D_{t-1} \,. \tag{3}$$

Since the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) looks at the asymmetric volatility that occurs in the variables studied, this model considers volatility under negative shock conditions ('bad news') and positive shock conditions ('good news'), where D is a Dummy with a value of 1=bad news/negative shock for $\mu_t < 0$, and a value of 0=good news/positive shock for $\mu_t > 0$. Good news (positive shock) has an impact β_1, while bad news (negative shock) has an impact $\beta_1 + \gamma_1$, and $\gamma > 0 =$ asymmetry, while $\gamma = 0 =$ symmetry (model collapses to the standard GARCH). If γ is significant and positive, negative shocks will have larger effects on $\frac{IDR}{USD_t}$ than positive shocks.

The Exponential GARCH (EGARCH) model was developed by Nelson (Dinga et al., 2023) to capture the leverage effects of shocks (policies, information, news, incidents, and events) on the financial market, And it allows for testing asymmetries. EGARCH can be used where time-varying volatility is a concern; an increase and decrease of the same magnitude can have different effects on its volatility. To do this, the log of the variance series is used. For monetary variable in the EGARCH method, the logarithm of the variance series is used to capture different volatility reactions depending on the moment when the economic shock occurs, either positively or negatively, see equation (4).

EGARCH Equation:

$$\mathrm{Log}\left(\frac{IDR}{USD_t}\right) = \propto + \sum_{i=1}^{q} \beta_i \left| \frac{u_{t-i}}{\sqrt{\frac{IDR}{USD_{t-i}}}} \right| + \sum_{i=1}^{q} \varepsilon_t \frac{u_{t-i}}{\sqrt{\frac{IDR}{USD_{t-i}}}} + \sum_{k=1}^{p} \theta_k \log\left(\frac{IDR}{USD_{t-k}}\right). \quad (4)$$

The EGARCH Equation above was specified as the conditional variance for the orders p, q model. Note that the log of variance series ($\frac{IDR}{USD_t}$) makes the leverage effect exponential rather than only quadratic as was in the previous GARCH model. This ensures that the estimates are non-negative. It is also important to note that ∝= constant, β=ARCH effects, ε=asymmetric effects and θ=GARCH effects. If all the ε equal zero ($\varepsilon_1 = \varepsilon_2 = 0$), then the model is symmetric, but if $\varepsilon_i < 0$, it implies that negative shocks generate larger volatility than positive shocks.

3.3. Diagnostic Test

Diagnostic tests are required in GARCH modelling to ensure the model accurately captures volatility clustering, validates model assumptions, and prevents misleading financial risk forecasts. These tests verify model specifications to select the optimal model for the estimation. For the standard GARCH method, it was essential to determine the stationarity of the data, in which the unit root test using the augmented Dickey Fuller test were conducted. Next, the correlogram test determined the orders of the model (p, q). The residual diagnostic heteroscedasticity test was conducted to accept H_0 or reject H_0, and then the study determined the length of conditional variance (R^2) to represent the orders.

Another essential step of diagnostic testing is to conduct the Ljung-Box test. It is particularly important for GARCH models to verify that there is no remaining autocorrelation in the conditional variance, which is essential because if there is autocorrelation detected in the residuals, it would mean that the model has not fully captured the data's structure. Thus, it would deem the models to be unfit. The goal was to verify that the models in this study were not mis-specified, and therefore the estimation can proceed (Abd Rahman et al., 2023; Tardiana et al., 2024; Li, 2023). This was conducted with all three models (GARCH, GJR-GARCH, and EGARCH) to provide model adequacy verification before estimation.

3.4. Estimation

For the estimation, the author applied the GARCH method and the ARCH LM test to reassure the heteroscedasticity state of the model. The final step was employing Forecast ARIMA (1,1,1) by choosing static forecast on the IDR/USD variable. For GJR-GARCH, the first step distinguishes the standard GARCH model by determining its threshold. , following the standard estimation using GARCH model. All the other initial steps, including the stationary test, the correlogram test, and the diagnostic residual heteroscedasticity test were all carried out before executing the GJR-GARCH approach. As for EGARCH, the estimation differentiated in the GARCH estimation step, determined the variance model to be EGARCH in the estimation setting, and making the asymmetric order equal to 1. The key in interpreting the EGARCH result would be focusing on the coefficients, because C (4) = constant, C (5) = ARCH coefficient, C (6) = asymmetric coefficient, and C (7) = GARCH coefficient.

3.5. Robustness Check

To ensure the consistency of all the model estimations, this study a conducted robustness check for the results. Using EViews as an analytical program, this paper implemented a robust standard error method using two steps, which were: Student-T distribution test and sub-period analysis for the model. Performing the robustness check was crucial to check whether the results were sensitive to the assumption of normality. If the results of these tests still showed positive and significant C (6) which represents the leverage effect, then it would be safe to conclude that the findings are robust, meaning that the conclusions would be supported by multiple methodologies and thus proved to be statistically stable and consistent.

For the sub-period analysis, this study had to categorise and identify major economic regimes that caused extreme changes in the IDR/USD exchange rate, producing several categories of sub-periods: during 2008-2009, a global financial crisis, during 2013-2014 when taper tantrum/quantitative easing in the USA took place, and lastly, during the Covid-19 pandemic in 2020-2021. The sub-period analysis conducted in all the periods between 2006-2025 in each macroeconomic crisis observed whether coefficient C (6) that reflected the leverage effect would be in the same condition as the model was ran with all the data without division into sub-periods.

Another test to ensure the robustness of the results could be conducted by comparing the in-sample and out-of-sample forecasting performance. This primarily acts to validate that the models generalise to new data and not only overfitting historical noise. Previous studies have assessed the estimation of volatility while also conducting in-sample and out-of-sample forecasting performance to ensure the forecasting accuracy of the GARCH models being studied (Chen, 2023; Nemushungwa, 2024). Accurate modelling and forecasting are crucial for evaluating volatility performance of exchange rates, especially in executing comparison between GARCH methods as proposed in this study.

4. Results

4.1. Diagnostic Test

For all the variations of the GARCH method, it was important to run the unit root test using the augmented Dickey Fuller test as a start to ensure the stationarity state of the data (see Table 1). It was revealed that variables were not stationary in Level, instead they reached stationarity in First Difference. This result fitted the standard criteria to be able to conduct estimation using the GARCH method. The significance level that was used as a standard test for this result was 5%.

Table 1. ADF Unit Root Test Result

Variable	ADF Statistics Level	ADF Statistics First Difference
Y (IDR/USD)	0.8494	*0.0000
W (JCI Index)	0.0961	*0.0001
X (Global Oil Price)	0.0157	*0.0000
Z (USD National Broad Index)	0.8680	*0.0001

Source: authors' calculations using EViews.

A correlogram test was conducted to determine the orders, after confirming that the data were indeed stationary. The p and q order that was used here held several meanings, where p represented the order from autoregressive component (AR), whereas q was for moving average component (MA). The significance level that was used as standard test in this result was 5%. The result was displayed in Table 2 below, which showed the probability of both AR (1) and MA (1) to be significant at less than 5%. This it can be concluded that the ARIMA used in this paper for mean equation was in the order of (1, 1, 1) with the order for AR=1 and the order for MA=1.

Table 2. Correlogram Test Result

Variable	Coefficient	Std. Error	t-Statistics	Prob.
AR(1)	-0.462016	0.063482	-7.277913	*0.0000
MA(1)	0.603368	0.057083	10.56997	*0.0000

Source: authors' calculations using EViews.

As explained beforehand, after selecting the order for mean equation to be (1, 1, 1), the step was running a hypothesis diagnostic for heteroscedasticity using a heteroscedasticity residual diagnostic test. The objective was to reject H_0 since this was a hypothesis test, hence it was vital to determine with which H_0 and H_1 to begin, respectively, where H_0 = homoscedasticity, and H_1 = heteroscedasticity. Thus, rejecting H_0 and accepting H_1 would mean that heteroscedasticity was detected in the model, being the fundamental reason why GARCH models were chosen to estimate exchange rate volatility in this study (see Table 3). It was found that probability for both F-Statistic and Obs*R-squared (Chi-Square) was significant in less than 5%. Based on these results, it was decided that this study cannot use the ARIMA approach and therefore GARCH was used instead.

Table 3. Heteroscedasticity Test: ARCH Result

F-Statistics	29.50516	Prob. F(1,5046)	*0.0000
Obs*R-squared	29.34527	Prob. Chi-Square(1)	*0.0000

Source: authors' calculations using EViews.

Subsequently, after obtaining the result for the rejected H_0, the next step was to determine the length of conditional variance, to establish the order for variance equation, particularly required for the standard GARCH model. The orders for all GARCH models were p, q (1, 1). Next, an analysis using the GARCH approach was carried out, see Tables 4 and 5 for residual diagnostic test. From the standard GARCH result, it was found that the probability for both AR and MA was less than the significance level of 1%. Thuis suggested that the historical data of residual terms can significantly affect the volatility of IDR/USD.

Table 4. Ljung-Box Diagnostic Test on Standardised Residuals

Lag	AC	PAC	Q-Stat	Prob.	Interpretation
1	0.001	0.001	0.0021	0.963	No autocorrelation
2	-0.011	-0.011	0.5059	0.777	No autocorrelation
3	0.072	0.072	24.005	0.000	Negligible
4	-0.028	-0.028	27.439	0.000	Negligible
5	0.008	0.010	27.737	0.000	Negligible
6	-0.025	-0.031	30.536	0.000	Negligible
7	-0.009	-0.004	30.869	0.000	Negligible
8	0.001	-0.002	30.871	0.000	Negligible
9	-0.038	-0.033	37.248	0.000	Negligible
10	0.044	0.044	46.077	0.000	Negligible
11	-0.013	-0.015	46.877	0.000	Negligible
12	-0.076	-0.071	73.249	0.000	Negligible
13	-0.003	-0.011	73.279	0.000	Negligible
14	-0.011	-0.008	73.867	0.000	Negligible

Lag	AC	PAC	Q-Stat	Prob.	Interpretation
15	0.025	0.033	76.740	0.000	Negligible
16	-0.004	-0.006	76.823	0.000	Negligible
17	0.013	0.016	77.575	0.000	Negligible
18	-0.002	-0.012	77.594	0.000	Negligible
19	0.003	0.008	77.648	0.000	Negligible
20	0.006	-0.000	77.827	0.000	Negligible
21	-0.008	-0.009	78.134	0.000	Negligible
22	-0.001	0.004	78.141	0.000	Negligible
23	0.003	0.002	78.196	0.000	Negligible
24	-0.030	-0.032	82.262	0.000	Negligible
25	0.002	-0.002	82.283	0.000	Negligible
26	0.001	0.001	82.292	0.000	Negligible
27	-0.001	0.005	82.301	0.000	Negligible
28	0.000	-0.001	82.302	0.000	Negligible
29	0.001	0.004	82.311	0.000	Negligible
30	0.002	-0.003	82.324	0.000	Negligible
31	0.001	0.003	82.332	0.000	Negligible
32	0.000	-0.001	82.333	0.000	Negligible
33	0.002	-0.000	82.349	0.000	Negligible
34	-0.005	-0.003	82.467	0.000	Negligible
35	-0.000	-0.000	82.467	0.000	Negligible
36	0.003	-0.002	82.496	0.000	Negligible

Source: authors' calculations using EViews.

To assess the adequacy of the GARCH models, this study applied the Ljung-Box Q test to the standardised residuals. Table 4 shows that all the autocorrelation coefficients were close to zero, with the largest value of -0.076 in lag 12. This indicates that the Ljung-Box Q test on standardised residuals showed no autocorrelation remains, and that the model was well specified. Even though the p-values for lag 3 upwards were <0.05, this would not automatically mean that the models possessed autocorrelation in the residuals, because EViews software stated "Probabilities may not be valid for this equation specification." This accounts for the fact that the dependent variable was lagged. In other words, while the probability values were adjusted for the presence of dynamic regressors and may not be individually reliable, the visual inspection of the autocorrelation function confirmed that the model adequately captured the dynamics in the data. The AC (autocorrelation coefficients) all showed the near zero value, and Q -Stat showed gradual increase rather than sudden spikes.

4.2. Estimation Findings

- Standard GARCH Model

Table 5. Standard GARCH Result

Variable	Probability	RESID(-1)²	GARCH(-1)
AR (1)	0.0000	0.0000	0.0000
MA (1)	0.0000	0.0000	0.0000

Source: authors' calculations using EViews.

Table 6 shows ARCH LM test result, or the residual diagnostic test to be exact, which was performed to discover whether the model was still heteroscedastic. The result showed that the F-Probability value of 0.0895 and Chi-Square value of 0.0895 both indicated that they did not meet the significance level of 5%, hence this result did not reject H_0, thus suggesting that the model was homoscedastic and no longer heteroscedastic.

Table 6. ARCH LM Test Result

Variable	F-Statistics (ARCH LM)	Chi-Square (ARCH LM)
WGT_RESID²(-1)	0.0895	0.0895

Source: authors' calculations using EViews.

The analysis proceeded to forecast the IDR/USD exchange rate after obtaining results from the GARCH and Residual Diagnostic tests. Figure 2 shows the static forecast, which demonstrated reasonable accuracy based on its error metrics. The Root Mean Squared Error (RMSE) was 0.034189 and the Mean Absolute Error (MAE) 0.021670; both low values signify small average forecast errors. Furthermore, the minimal Inequality Coefficient (IC) of 0.001820 confirms this assessment, as a value near zero indicated a low degree of forecast bias, serving as evidence that the forecasting result in this study was sound and reliable.

As for the forecasting result, the trend of IDR/USD in Figure 2 showed an upward trend over time. In this case, an upward trend line was not a good indicator for the performance of IDR/USD for Indonesian economy, because the upward curve indicated a depreciation of the currency. A prolonged depreciation would not look good for Indonesia's macroeconomic performance, particularly in the monetary sector. Meanwhile, the forecasting result for the variance demonstrated clustering volatility over time, although it showed a decline in fluctuations as the years progressed.

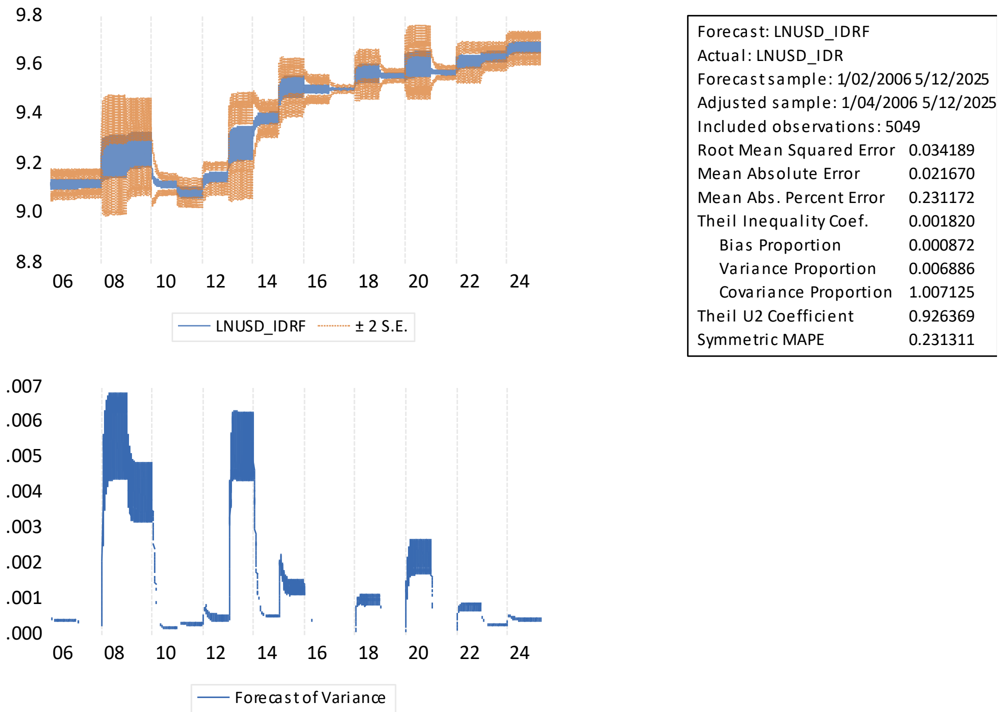


Fig. 2. Forecasting of IDR/USD Result

Source: authors' computations using EViews.

- GJR-GARCH Model

Regarding GJR-GARCH, the assumption tests were run in an identical manner as the other GARCH models. After the model passed the stationary test using the unit root test (ADF test), the correlogram test, and the heteroscedasticity test, the study proceeded with adding threshold for the GARCH estimation method. Note that the threshold (equal to 1) was added after running the standard GARCH estimation test. Table 7 shows the result of the GJR-GARCH estimation, which included a coefficient of -0.330682 with the probability passing the significance level of 1%.

Table 7. GJR-GARCH Estimation Result

Variable	Coefficient	Std. Error	t-Statistics	Prob.
C	0.000487	3.88E-05	12.55845	0.0000
RESID(-1)^2	0.296458	0.004587	64.63023	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.330682	0.004941	-66.93024	0.0000
GARCH(-1)	0.600222	0.026484	22.66387	0.0000

Source: authors' calculations using EViews.

The coefficient of the asymmetric term was -0.330682 and statistically significant at the level 1%, which indicated that for this variable there were asymmetries in the volatility. The negative coefficient indicated that positive shocks (good news) have larger effects than negative shocks (bad news). This means $\beta_1 + \gamma_1 < \beta_1$.

For positive shocks, the estimate of the time-varying volatility was:

$$\frac{IDR}{USD_t} = 0.000487 + 0.600222\frac{IDR}{USD_{t-1}} + 0.296458\mu_{t-1}^2$$

and for negative shocks, the estimate of the time-varying volatility was:

$$\frac{IDR}{USD_t} = 0.000487 + 0.600222\frac{IDR}{USD_{t-1}} + (0.296458 - 0.330682)\mu_{t-1}^2 ,$$

while 0.296458 stands for symmetry, and 0.330682 represents asymmetry. The difference between good (positive) and bad (negative) shocks on the IDR/USD variable was 0.330682, i.e. the coefficient of asymmetric term γ. Hence one can conclude that in this model economic shocks are incredibly significant determinants of assets' volatility.

- EGARCH Model

As well as for the previous standard GARCH model and GJR-GARCH model, estimating IDR/USD volatility using EGARCH approach was conducted after passing the stationary test using the unit root test (ADF test), the correlogram test, and the heteroscedasticity test. The EGARCH estimation was run by finishing standard the GARCH estimation first, and proceeded with determining asymmetric order equal to 1, as well as changing the estimation format into the EGARCH method. The result is shown in Table 8, which presents coefficients of the asymmetric term in the model.

Table 8. EGARCH Variance Equation Result

Variable	Variance Coefficient	Variance Std. Error	Variance z-Statistics	Variance Prob.
C(4)	-2.537375	0.110067	-23.05296	0.0000
C(5)	0.269885	0.028498	9.470162	0.0000
C(6)	0.366168	0.012640	28.96991	0.0000
C(7)	0.648595	0.014155	45.82235	0.0000

Source: authors' calculations using EViews.

Table 8 provides some key points, which were the coefficients as following: C (4) = $\propto$; C (5) = β; C (6) = ε; C (7) = θ, where C (4) stands for constant, whilst C (5) for ARCH coefficient, while C (6) stands for asymmetric coefficient, and C (7) for GARCH coefficient. The main points of this result were these four coefficients, which represented the response or reaction of different volatility that IDR/USD presented over time. Therefore, the coefficient of the asymmetric term was positive (0.366168) and statistically significant at the 1% level. In exponential terms, C (6) = $\varepsilon = e^{0.366168} = 1.442197511$ which indicates that for IDR/USD, negative shocks have a stronger effect on the volatility of the exchange rate than positive shocks.

In EGARCH, calculating total leverage effects was required to investigate the total effect on the coefficient on the logarithm of an independent variable, which in this case is IDR/USD. The assumptions were as follows:

- If $u_{t-i} < 0$, the total effect of u_{t-i} on $\log(\frac{IDR}{USD_t})$ is: $(1 - \varepsilon_1)|u_{t-1}|$. Less than zero means negative, and in this context, it means the Indonesian IDR (IDR) appreciated unexpectedly against the US Dollar (USD), or the USD depreciated unexpectedly.
- If $u_{t-i} > 0$, the total effect of u_{t-i} on $\log(\frac{IDR}{USD_t})$ is: $(1 + \varepsilon_1)|u_{t-1}|$ More than zero means positive, hence the IDR depreciated unexpectedly against the USD, or the USD appreciated unexpectedly.

Since ε was 0.366168, thus more than 0, therefore the the total effect of u_{t-i} on $\log(\frac{IDR}{USD_t})$ was: $(1 + \varepsilon_1)|u_{t-1}|$. This would mean that for IDR/USD, negative shocks had larger effect on the volatility of the stock than positive shocks.

4.3. Robustness Check

Robustness Check Using the Student's t-Distribution Test.

To ensure the robustness of the EGARCH model results, the author used Student t-distribution test. Table 9 showed that the EGARCH model with this distribution was highly significant and demonstrated that the IDR/USD exchange rate exhibited remarkably high volatility persistence and a strong, significant leverage effect. The low degrees of freedom parameter confirmed that returns had very fat tails, meaning extreme events were more common than a normal distribution would predict. This model is a significant improvement over this study's previous GARCH models with a normal distribution.

Table 9. Robustness Check Using Student-T Distribution

Parameter	EGARCH (Normal)	EGARCH (Student's T)
C (Mean)	0.003917	0.001803
C(4) (Variance Constant)	-2.537375	-0.235836
C(5) (ARCH coefficient)	0.269885	0.038222
C(6) (Leverage Effect)	0.366168	0.390648
C(7) (GARCH/Persistence)	0.648595	0.971792
Degrees of Freedom	-	3.597314
Log-Likelihood	10057.24	11601.38
AIC	-3.981083	-4.592231
SIC	-3.972034	-4.584476

Source: authors' calculations using EViews.

Moreover, Table 9 revealed that constant (C) equalled 0.001803 with a highly significant p-value of 0.0000. This indicated a positive and significant daily exchange rate, even though relatively small. Next, the variance equation from the EGARCH version using the Student t-distribution result was as follows:

$$\log(\sigma_t^2) = -0.235836 + 0.038222\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + 0.390648\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + 0.971792\log(\sigma_{t-1}^2).$$

Key notions from the variance equation above was that constant C (4) showed a high significance at -0.235836, which is the baseline level of log-variance. The ARCH coefficient in C (5) was equal to 0.038222 with a positive and significant p-value at 0.0005. This confirmed that large shocks, regardless of positive or negative, increased future volatility (the classic volatility clustering effect). The leverage effect in C (6) was at 0.390648, and with a positive and highly significant p-value at 0.0000. These results confirmed that negative shocks (depreciation of IDR) increase future volatility significantly more than positive shocks (appreciation of IDR) of the same magnitude.

Meanwhile, the EGARCH model was reflected by C (5) which was a representation for persistence in the model. The value of C (5) was 0.971792, which indicated that for this coefficient, the number was remarkably close to 1 and highly significant. This would mean that volatility of IDR/USD was highly persistent and reverted very slowly whenever fluctuations happened. Compared to the previous EGARCH model without the Student t-distribution test, this version provided higher normal-distribution number, thus it suggested that this model was not underestimating volatility persistence unlike the previous EGARCH model.

- Robustness Check Using Sub-Period Analysis

Table 10. Robustness Check Using Sub-Period Analysis

Sub-Period	Leverage (C(6))	Significance	EGARCH/Persistence (C(7))	Significance
Full Sample (2006-2025)	0.366168	0.0000	0.648595	0.0000
Global Financial Crisis (2008-2009)	0.516309	0.0000	0.736707	0.0000
Taper Tantrum (2013-2014)	1.408250	0.0000	0.031976	0.0000
COVID-19 (2020-2021)	0.379253	0.0001	0.798210	0.0000

Source: authors' calculations using EViews.

By incorporating the sub-period sample into the EGARCH model, this study evaluated the stability of the asymmetric volatility phenomenon across different macroeconomic regimes. Table 10 shows the EGARCH estimation results for sub-periods by dividing the period into the Global Financial Crisis, the Taper Tantrum, and the COVID-19 pandemic. The result showed that coefficient C (6) which represented the leverage effect was consistently positive and significant across all the sub-periods, demonstrating the robustness of this study's main findings. The same also occurred for coefficient C (7) which stood for EGARCH/persistence of the model, which was also positive and significant across all sub-periods.

- Robustness Check Using In-Sample and Out-of-Sample Forecasting

Another method to validate the robustness of the findings is critical to ensure the reliability of the model. While in-sample forecasting was conducted to verify that the model fit the historical data patterns, out-of-sample forecasting was carried out to ensure the model was not overfitting or only reacting to white noise. Figure 3 reveals that Root Mean Squared Error (RMSE) showed 0.041815, which indicates a very small forecast error, and both Mean Absolute Error (MAE) and Mean Abs. Percent Error (MAPE) was close to 1%, and the Bias Proportion showed only 0.16% of error in systematic bias. The results confirmed that the model fits the in-sample data and that its specification captures the underlying dynamics accurately.

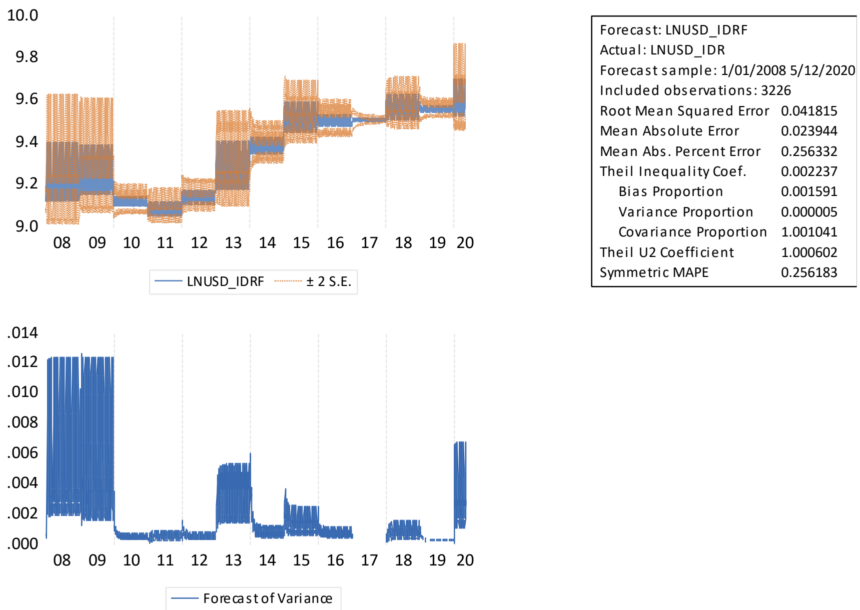
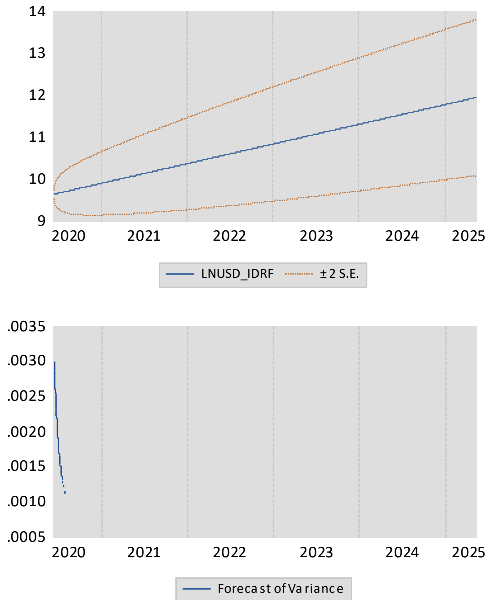


Fig. 3. In-Sample Forecasting Result

Source: authors' computations using EViews.

Regarding the out-of-sample forecasting, Figure 4 shows that Root Mean Squared Error (RMSE) was 1.308604, a relatively high number. Mean Abs. Percent Error (MAPE) also delivered higher results than the in-sample forecasting, which was 12% average. Bias proportion in particular showed a very high number of 0.766372, which reflected a huge proportion of systematic bias, and not sporadic bias. It should be noted that the period sample for out-of-sample forecasting was after the 2020Covid 19 pandemic, in which fluctuations in economic indicators were found to be common. Another important result was that the range for IDR for the period after 2020 was increasing, ranging from 12,000 to 16,000 IDR/USD, higher than the period before 2020.



Forecast: LNUSD_IDRF	
Actual: LNUSD_IDR	
Forecast sample: 6/12/2020 5/12/2025	
Included observations: 1282	
Root Mean Squared Error	1.308604
Mean Absolute Error	1.145900
Mean Abs. Percent Error	11.88683
Theil Inequality Coef.	0.064118
Bias Proportion	0.766372
Variance Proportion	0.225189
Covariance Proportion	0.008439
Theil U2 Coefficient	48.45215
Symmetric MAPE	11.04060

Fig. 4. Out-of-Sample Forecasting Result

Source: authors' computations using EViews.

Even though the in-sample forecasting result showed a remarkable accuracy for the model to predict IDR based on the historical pattern of the data, the out-of-sample forecasting resulted in an extremely volatile movement. Based on Figure 4, it can be concluded that IDR depreciated more than the historical pattern would suggest, therefore the out-of-sample forecasting result showed an under-prediction performance for IDR in the period after 2020. In short, to assess the predictive performance of the EGARCH model, the author conducted both in-sample forecasting and out-of-sample forecasting. The in-sample forecast used the period 2008-2020 which depicted excellent fit and a bias proportion near zero, while the out-of-sample forecast result showed a systematic bias of 76%, a very high number that indicates heightened uncertainty during the post-pandemic period.

4.4. Implications

The author revealed the three key findings. Firstly, the GARCH method did not define between good news and bad news in the volatility of exchange rates. GJR-GARCH was asymmetrical and EGARCH was logarithmic, thus these methods delivered the result 'better' in terms of giving clearer context of the volatility. Second, although GJR-GARCH provided more explanations on the volatility, this method produced a negative coefficient in the results. This is theoretically implausible where a negative coefficient could not occur, because they violate the fundamental requirement that conditional variance must remain positive. Both the impacts of past shocks and persistence of volatility must be non-negative. This implies a positive restraint for the GJR-GARCH model. The potential reasons for this might come from the leverage effect, which indicated its absence. The negative coefficient suggests that the leverage effect is not present, and it is statistically significant with a p-value of 0.000. Furthermore, this issue does not arise when using the EGARCH method, hence it further proved that the EGARCH method is more reliable, and was in line with similar research findings regarding this matter (Almisshal, 2021).

The third finding concerns policy implications. The results from EGARCH after it passed robustness check tests showed that the IDR/USD market is not only volatile, but predictably and asymmetrically volatile. It reflected the difference between the impact of bad news to its volatility, rather than when it showed positive news. Therefore, the central bank in Indonesia could not address exchange rates volatility symmetrically in its approach. When a market's persistence is high, it showed that a shock in the exchange rate could last for longer, and served as evidence that the market's fear of depreciation is higher than its favourable perception of exchange rates appreciation. By approaching this situation with asymmetric policy, it would mean that Bank Indonesia as the central bank should respond to depreciation more seriously than to appreciation, because of the risk of it lasting longer. Increasing the interest rate is a way for Bank Indonesia to let the flow of money come into the country, although it does create risk for the domestic economy. The main objective for this is to prevent the depreciation of IDR to sustain for longer periods of time.

An asymmetric policy for the Bank of Indonesia means that it applies different treatment regarding different performance of IDR. A weakening IDR requires more attention than a strengthening one. This does not imply that the Bank of Indonesia should neglect an appreciation, but instead it requires to ensure that the appreciation is relatively stable, in line with previous research regarding an asymmetric monetary policy (Ca' Zorzi et al., 2023; Ülke & Berument, 2016). The longer IDR depreciation persists, the longer the market will suffer. This will also create a monetary dilemma for the Bank of Indonesia, because when it raises interest rates to combat depreciation, economic growth will suffer (Utami et al., 2025). This would affect the economy structurally, not only temporarily even though the situation was initiated from a negative shock (Kim et al., 2019). The core objective for the Bank is inflation targeting, and not exchange rate volatility control, however ignoring the persistence of depreciation will also create more burden for the economy later.

5. Discussion and Conclusions

This study applied three GARCH models, namely the standard GARCH model, the GJR-GARCH model, and the EGARCH model on the volatility of the IDR/USD exchange rate, using symmetric, asymmetric, and logarithmic assumptions on each method. The result revealed that in the GARCH method, there was high persistence of volatility, and the shocks showed indication of long-lasting duration, but the model was symmetrical. Meanwhile, the GJR-GARCH model showed indications that negative shocks have larger effects than negative shocks on IDR/USD but with problematic negative coefficients. Lastly, in the final comparison it was found that the EGARCH specifications were the most reliable in capturing asymmetric volatility dynamics, with strong evidence of leverage effects where negative shocks increase future volatility more than positive shocks.

Based on the result, it could be concluded that as the IDR/USD volatility took a long time to dissipate, and negative shocks had significantly larger effect than the positive shocks, it meant that the market reacted strongly to depreciation rather than to appreciation. Therefore, it has become essential for policymakers in Indonesia to provide an asymmetrical policy framework to prevent the negative shocks to sustain into a prolonged period of distrust by the market towards IDR. Such actions could be established by reacting more strongly to handle depreciation and to prevent it from prolonging into a long period of depreciation. One of these actions could be to increase interest rates, a preventive action to respond to depreciation, and at the same time acknowledging the asymmetric approach for responding to depreciation.

The monetary trilemma for the Bank of Indonesia as the central bank, would be to ensure price stability, economic growth, and a stable exchange rate, all of which requires a strong coordination of Indonesia's monetary and fiscal policy. Policymakers can not only focus on stabilizing IDR volatility without addressing trade-off risks from other economic indicators. While implementing asymmetric monetary policy, policymakers are encouraged to implement countercyclical fiscal policy to combat economic slowdown caused by interest rates hikes (from monetary policy). As Indonesia's domestic consumption exceeds 50% of GDP, protecting purchasing power of households is essential. Central bank credibility in Indonesia does not only depend on inflation rate stability, but also the welfare of households despite the volatility, as shown in the author's previous research. Therefore, it is not recommended to cut growth spending, because it would only prolong the economic slowdown.

As for the methods used, it was clearly indicated from the results that the EGARCH model was the best approach to capture volatility without ignoring the differences of the model's impact when IDR/USD depreciates or appreciates. By running the standard GARCH model, the leverage effect was not acknowledged. While GJR-GARCH incorporated this issue using asymmetric assumption in its executions, this model could produce negative coefficient for volatility, which should not happen statistically, as was also confirmed in this study. During the robustness check, it was discovered that the EGARCH method proved superior to the other GARCH models, and therefore the results presented before were all stable and accurate.

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Porównanie modeli symetrycznych, asymetrycznych i logarytmicznych z wykorzystaniem metod GARCH, GJR-GARCH i EGARCH w prognozowaniu zmienności waluty Indonezja–USA

Streszczenie

Cel: Głównym celem tego badania jest przedstawienie porównania modeli GARCH, którymi są standardowy model GARCH, asymetryczny model GJR-GARCH oraz logarytmiczny model EGARCH dotyczący zmienności kursu walutowego (IDR/USD).

Metodyka: Autorzy wykorzystali GARCH, Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) oraz Exponential GARCH (EGARCH) do oszacowania i prognozowania zmienności kursu walutowego. Zmiennymi są IDR/USD, indeks giełdy papierów wartościowych w Dżakarcie (JCI), światowa cena ropy naftowej oraz indeks nominalnego szerokiego dolara amerykańskiego. Dane pochodziły z Banku Światowego, Federal Reserve Economic Data i Indonesian Stock Exchange z lat 2006-2025 i były gromadzone codziennie.

Wyniki: Analiza wykazała, że w modelu GARCH występowała wysoka trwałość zmienności, a szoki miały charakter długotrwały; model ten był jednak symetryczny. Z kolei model GJR-GARCH wskazywał, że szoki negatywne mają większy wpływ na kurs IDR/USD niż szoki pozytywne, choć pojawił się problem ujemnych współczynników. Ostatecznie porównanie modeli wykazało, że specyfikacje EGARCH były najbardziej wiarygodne w uchwyceniu asymetrycznej dynamiki zmienności, dostarczając silnych dowodów na występowanie efektu dźwigni, zgodnie z którym szoki negatywne zwiększają przyszłą zmienność bardziej niż szoki pozytywne.

Implikacje i rekomendacje: Ponieważ zmienność IDR/USD wykazywała wysoką trwałość, a szoki negatywne oddziaływały na nią znacznie silniej niż pozytywne, oznacza to, że rynek reagował bardziej na deprecjację niż na aprecjację. W związku z tym dla decydentów w Indonezji kluczowe stało się opracowanie asymetrycznych ram polityki, aby zapobiec przekształceniu się negatywnych szoków w długotrwały okres braku zaufania rynku wobec IDR. Jednym z działań było podniesienie stóp procentowych. Było to działanie prewencyjne, mające na celu reakcję na deprecjację, a jednocześnie uwzględniające asymetryczne podejście do reagowania na deprecjację.

Oryginalność/wartość: Badanie porównuje trzy modele GARCH w celu analizy i prognozowania zmienności kursu IDR/USD, wskazując model najbardziej wiarygodny pod względem statystycznym i ekonomicznym, co stanowi o jego unikatowości. Uzyskane wyniki przedstawiają kompleksowe i metodologicznie uzasadnione porównanie, które ma charakter obiektywny oraz ukazuje ograniczenia i mocne strony każdego z modeli. Badanie wnosi również dodatkowy wkład poprzez integrację zmiennych o szerokim charakterze do modeli, z wykorzystaniem światowych cen ropy naftowej, indeksu JCI oraz nominalnego szerokiego indeksu dolara amerykańskiego.

Słowa kluczowe: zmienność, GARCH, GJR-GARCH, EGARCH, kurs walutowy, szoki negatywne